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Article · June 2014

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An Overview of Artificial General Intelligence as of 2014

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1. Introduction¹

In this article, the term “Artificial General Intelligence” (AGI hereafter) refers to artificial intelligence (AI) being general in the sense that it is designed not for particular tasks but for being capable of learning various skills. The article reviews approaches and prospects for AGI.

At its beginning, the discipline of AI aimed for realizing general cognitive functions similar to human intelligence. What a non-AI-expert might think of with the term “artificial intelligence” would also be something similar to human intelligence. However, attaining such intelligence was much harder than it had been imagined.

“The Good Old-Fashioned AI (GOFAI)” assumed that general intelligence would be realized with symbol processing (the physical symbol system hypothesis). Earlier cognitive architectures aiming for general intelligence such as Soar [Laird 12] were based on this hypothesis. This approach involves, as it has been pointed out, issues such as the frame problem and the issue of classical categories², and it is also known for not being so good at acquiring knowledge (learning).

The connectionist approach using non-symbolic or sub-symbolic computation has as long history as GOFAI. While this approach mainly focuses on learning, it has not been so good at dealing symbols, logic and language, and has not realized AGI either.

As the realization of AGI was not anticipated in the near future, the mainstream researches in AI shifted to the “narrow AI” [Kurzweil 05] that aims for creating systems that exhibit particular intelligent behaviors in particular contexts.

As the turn of the 21st century, the interest for AGI has been reemerging. In 2006, an anthology on AGI [Goertzel 06] was published and the AGI conferences³ have been held since 2008. On the background lie the increase in computing power and the development of brain science, learning theories, and robotics. Moreover, certain recent AI technologies such as IBM’s Watson⁴ and self-driving cars such as those by Google have demonstrated themselves as successful and appeared to be promising as stepping-stones to AGI.

2. Issues with the realization of AGI

Challenges such as the following have been pointed out with regard to the realization of AGI.

2.1 The Frame Problem

According to the formulation by Dennett [Dennett 84], the frame problem involves impractically long computation time for the retrieval and selection of information necessary (or relevant) for taking actions. While it is not clear that this problem is inherent to systems based on the physical symbol system hypothesis or similar frameworks, one might argue that the problem could be evaded with systems based on sub-symbolic association that presents most relevant information first.

2.2 The Symbol-Grounding Problem

The symbol grounding problem is the problem of how a symbol obtains its meaning in relation with the world. It involves the issue of linking symbols with sensory information from the exterior world within artifacts such as robots.

¹ This article is an expanded version of an article written in Japanese as an introduction to AGI for the audience at the 2014 conference of the Japanese Society for Artificial Intelligence [Arakawa 14].
<https://kaigi.org/jsai/webprogram/2014/paper-174.html>

² For example, the membership of categories we use is often determined not in a crisp way but fuzzily depending on the distance from ‘prototypes.’ [Lakoff 90] [Gärdenfors 04].

³ <http://agi-conf.org/>

⁴ <http://www.ibm.com/smarterplanet/us/en/ibmwatson/>

2.3 Language Use

While language use would be a specific function if conceived as an innate function, as cognitive linguists such as Pinker purport [Pinker 94], it is also conceived as generic, for language and logic have close relationship [Allwood 77], and logic is thought to be something universal. For symbolic AI, the issue of non-classical categories in natural language² is an issue, and for sub-symbolic AI, the generativity (the potential to generate infinite patterns from finite rules) of language [Arakawa 13] is an issue. Ambiguity resolution has always been a grand practical challenge for natural language processing.

2.4 Imagination

It is pointed out that the capability of representing things that are not present such as things in the past, future or remote places is unique to human beings as opposed to other animals [Fauconnier 03]. Fauconnier et al. (ibid.) argue that *conceptual blending* in imagination is the essence of human mental life. It would be also obvious that imagination is related to theory of mind for understanding the mind of others, and social intelligence, which should be part of general intelligence, depends on imagination and linguistic competence. Thus, giving human-like imagination to machines would be a key for endowing them a human-level intelligence.

2.5 Computational complexity

The amount of computation required for intelligent behavior has been a grand issue to build practical AI systems. The frame problem mentioned above poses a theoretical challenge on computability, especially for symbolic logic-based AI. Many of search algorithms that would be useful for AI are found to be intractable. Sub-symbolic approaches are also not immune to computational complexity. Connectionist approaches often require massively high-dimensional computation, and statistical approaches such as the Bayesian approach sometimes require intractably massive computation to obtain probabilistic distributions.

3. Major approaches toward AGI

3.1 Cognitive Architecture

The discipline of AI has been studying/developing *cognitive architectures* to model (human) comprehensive cognitive functions since its early days, and numerous architectures such as Soar and ACT-R⁵ have been proposed⁶. For AGI necessarily involves comprehensive cognitive functions, a number of cognitive architectures such as OpenCog⁷ have been discussed at the AGI conferences.

Planning is one of the featured functions in cognitive architectures, which searches action series from the current status to the goal status. Large-scale planning involves the issues of a large amount of computation and situation change after initial planning. To deal with these problems, the BDI architecture [Rao 91] has been proposed, where the architecture substantiates abstract intentions (sub-goals) stepwise as required in plan execution.

3.2 Cognitive Robotics

AGI is expected to solve problems intelligently when it is embodied in the environment where human beings live and to develop its own cognitive functions like human infants. Thus, the research of cognition and cognitive development with robots is important for AGI and robots would be good test beds for AGI research. Moreover, embodiment should be important for challenging the symbol-grounding problem. There are, for example, projects in developmental cognitive robotics^{8, 9, 10}, the special interest group for SocioIntelliGenesis¹¹, and the community of

⁵ <http://act-r.psy.cmu.edu/>

⁶ Comparative Table of Cognitive Architectures: <http://bicasociety.org/cogarch/architectures.htm>

⁷ <http://opencog.org/>

⁸ http://www.er.ams.eng.osaka-u.ac.jp/asadalab/index_en.html

⁹ <http://www.isi.imi.i.u-tokyo.ac.jp/>

¹⁰ <http://naotoiwahashi.jp/>

¹¹ <http://www.sociointelligence.org/>

symbol emergence robotics¹² in Japan, and cognitive robotic platforms such as iCub¹³ and researches of communicative robots such as those at CNRS¹⁴, VUB¹⁵ and Jido¹⁶ overseas.

3.3 Machine Learning

Learning is an indispensable part of AGI, for a system that repeats the same mistake would not be called intelligent. The emerging mainstream of machine learning is the sub-symbolic approach that employs statistical (mostly Bayesian) theories. The connectionist approach, which is originated from neural network models such as perceptron, has been integrated into the statistical learning theories [Bishop 06]. Moreover, the approach where the brain itself is interpreted with the Bayesian statistics has emerged (see [Doya 06] and [Ichisugi 10]).

In recent years, deep learning, which uses multi-layered neural network models like cerebral neo-cortex, has been successful with pattern recognition tasks [Bengio 09]. As AI research has not attained human-level pattern recognition, development in this area is thought to be quite important for the realization of AGI.

With *reinforcement learning*, the agent learns ‘policies’ to maximize the average reward without being given stepwise reward in an uncertain environment by trial-and-error [Sutton 00]. Integration of deep learning and reinforcement learning is one of the hottest areas in machine learning (e.g., [Mnih 13]).

3.4 AGI inspired by the Brain

Many of the cognitive functions of the brain have not been realized on digital computers. While the brain has not been understood so much as we can emulate it to build a brain-like computer, it could give us important clues for creating AGI. There are two approaches inspired by the brain: one is the artificial brain approach that tries to emulate the entire brain, and another is neuro-computing that tries to realize partial computational functions of the brain.

The artificial brain approach¹⁷ can be divided to the large-scale brain simulation approach focusing on the biological findings [Garis 10], and Biologically Inspired Cognitive Architectures (BICAs) focusing on computational aspects [Goertzel 10].

Examples of large-scale brain simulation are Blue Brain Project¹⁸ at EPFL, Cognitive Computation Project¹⁹ by DARPA-IBM, and Neurogrid Project²⁰ at Stanford University. A roadmap [Sandberg 08] expects the whole brain emulation will be done by the middle of this century.

BICA researches are often concerned with hippocampus or cerebral neo-cortex. For example, NOMAD, the navigating robot, implements hippocampal functions as Brain-Based Devices [Fleischer 07]²¹. Ball et al. have made public their algorithm that simultaneously performs self-location and environmental map creation (SLAM) by emulating the hippocampus of rodents [Ball 13]. Ogawa et al. have proposed the Functional Parts Combination model for meta-learning that promptly reuses past experience, inspired by the understanding of brain functioning [Ogawa 05]. Moreover, Ichisugi et al. have begun considering the Whole-Brain Architecture (WBA), where cerebral organs are interpreted as machine learning devices to be integrated [Ichisugi 14]²².

Neuro-computing is a computational approach inspired by neural networks. As the functions of cerebral organs have been (though incompletely) identified in recent years, one could now pursue an approach in which a neural circuit that performs certain computation of interest would be identified and utilized as reference to discover new computational ways. Yamakawa calls such an approach ‘Theory-guided Neuro-Computing (TgNC).’ He assumes a basic computational function to solve the frame problem in the hippocampus and tries to discover a new algorithm, focusing on its informational representation [Yamakawa 12].

¹² <http://www.em.ci.ritsumei.ac.jp/en-research/> for example.

¹³ <http://www.icub.org/>

¹⁴ <http://pfdominey.perso.sfr.fr/RobotDemos.htm>

¹⁵ <http://ai.vub.ac.be/> lead by Luc Steels

¹⁶ <http://www.laas.fr/robots/jido/data/en/supervision.php>

¹⁷ <http://www.artificialbrains.com/>

¹⁸ <http://bluebrain.epfl.ch/>

¹⁹ <http://www.research.ibm.com/cognitive-computing/neurosynaptic-chips.shtml>

²⁰ <https://www.stanford.edu/group/brainsinsilicon/>

²¹ Used for the RoboCup competition, e.g., in the late 90’s.

²² <https://staff.aist.go.jp/y-ichisugi/brain-archi/j-index.html>

The cerebral neo-cortex is known to have a mostly uniform neural circuitry while realizing various functions in its areas [Mountcastle 82]. Thus, it is expected that the understanding of its mechanism would pave a road to AGI and attention has been gathered in this area [Hawkins 04] [George 09].

3.5 Language Use

The language use by machines has been studied in the fields of computational linguistics and natural language processing mainly from the viewpoint of symbol processing, where linguistic expressions are parsed and generated following certain (grammar) rules. Mechanical processing of linguistic expressions following rules is not so difficult unless it incurs disambiguation. Disambiguation, spanning from the phonetic level to the discourse level ([Asher 03]), is a challenging task, though numerous statistical methods for solution have been proposed. Full disambiguation may require ‘really understanding’ the meaning of linguistic expressions, where lie the issues of non-classical categories and symbol grounding (see § 2). Embodiment (i.e., research with robots in the context of AI) would be a key to overcome the challenge, as cognitive linguists such as Lakoff would argue.

3.6 Universalist AI

There are on-going debates on conceptual issues at the AGI conferences, and one of such issues is called ‘Universalist AI’ [Hutter 05], where ultimate intelligence is mathematically formalized with ideas from Occam’s razor and reinforcement learning. While the theory is not computable (practical), it has been discussed as the limiting case of general intelligence.

4. The Road Ahead

4.1 Roadmaps

An AI Magazine article entitled “Mapping the Landscape of Human-Level Artificial General Intelligence” [Adams 12] discusses a roadmap for AGI, where a roadmap (landscape) is defined by referring to human cognitive development. The OpenCog (see § 3.1) project also defines roadmaps referring to cognitive development²³.

The AI Magazine article [Adams 12] emphasizes the importance of collaboration among researchers. In fact, the issues discussed here involves numerous disciplines such as cognitive architecture, robotics, pattern recognition, machine learning, (cognitive/computational) linguistics, (cognitive) psychology, and brain sciences, whose knowledge should be integrated to realize AGI. AGI researchers in these domains are not only required to collaborate, but also would have to gain basic knowledge in domains other than one’s own expertise for better result.

As a benchmark for AGI, the Turing test was proposed in the founding days of AI, and annual Loebner prize contests are held as its concrete form²⁴. However, as the criterion of the Turing test is to deceive human beings by being indistinguishable over text chat, it is not to measure the generality of AI; it does not measure the capability of AI in non-text modality or embodiment. As for benchmarks of embodied AI, there are contests for robots represented by RoboCup. In particular, RoboCup@Home²⁵ requires performance in complex tasks involving interaction with human beings.

4.2 Predicting the advent of AGI

Ray Kurzweil claims that ‘the Singularity’ (the moment in which AI attains enough generality to create artifacts having higher intelligence) is near, stating that the development of information science advances exponentially (The Law of Accelerating Returns), brain science is an information science, and brain structure such as that of cerebral cortex has been identified [Kurzweil 12]. However, he has not given a concrete recipe for AGI.

There were questionnaires held for AI researchers from 2009 to 2011, according to which they predicted AGI would occur in a few decades. However, according to a survey [Armstrong 12], experts have constantly predicted that AGI would occur in decades ahead over the past decades²⁶. If one is to make a prediction better than a simple

²³ <http://wiki.opencog.org/wiki/home/images/3/39/Preschool.pdf>
<http://wiki.opencog.org/w/OpenCogPrime:Roadmap/>
<http://opencog.org/roadmap/>

²⁴ <http://www.loebner.net/Prize/loebner-prize.html>

²⁵ <http://www.robocupathome.org/>

²⁶ cf. “How long until human-level AI? Results from an expert assessment”
http://sethbaum.com/ac/2011_AI-Experts.html

See also <http://hplusmagazine.com/2011/09/16/how-long-till-agi-views-of-agi-11-conference-participants/>

expectation, an inventory of cognitive functions and methods to realize them would have to be made to give a ‘fit-gap’ analysis.

5. Invitation to AGI Research

5.1 Communities

International conferences such as the AGI conferences, BICA²⁷ and Advances in Cognitive Systems²⁸ are being held. There are communities of AGI researchers such as the AGI Society²⁹, Machine Intelligence Research Institute³⁰, and OpenCog (see § 3.1 & § 4.1). Social impacts with AGI have been discussed in communities such as Singularity University³¹, the Future of Humanity Institute³², and Humanity+³³. In Japan, there are communities related to AGI such as the AGI special interest group³⁴, the WBA (see § 3.4) community, and the special interest group for SocioIntelliGenesis³⁵. Those studying related topics are encouraged to participate in these activities.

5.2 Expectation for research in Japan

Embodiment, or research with robots, is a key, accelerating aspect for the realization of AGI. In Japan, advanced researches are carried out in the area of cognitive robotics (see § 3.2). The issue of symbol grounding has also been studied under the name of symbol emergence in robotics.

Seminars³⁶ on WBA (see § 3.4) have been held since 2013, based on the recent accumulation of findings in neuro-science and the maturity of machine learning such as deep learning, to discuss methodologies from WBA and TgNC (see § 3.4) for the realization of AGI.

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²⁷ <http://bicasociety.org/>

²⁸ <http://www.cogsys.org/>

²⁹ <http://www.agi-society.org/>

³⁰ <http://intelligence.org/>

³¹ <http://singularityu.org/>

³² <http://www.fhi.ox.ac.uk/>

³³ <http://humanityplus.org/>

³⁴ <http://www.sig-agi.org/>

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